

Ranking Online Services by Aggregating Ordinal Preferences

Ying Chen¹, Xiao-dong Fu^{1,2(✉)}, Kun Yue³, Li Liu^{1,2}, and Li-jun Liu^{1,2}

¹ Kunming University of Science and Technology, Kunming, Yunnan, China
578922532@qq.com, xiaodong_fu@hotmail.com

² Yunnan Provincial Key Laboratory of Computer Application, Kunming, Yunnan, China

³ Yunnan University, Kunming, Yunnan, China
kyue@ync.edu.cn

Abstract. With the increase of the number of online services, it is more and more difficult for customers to make the decision on service selection. Services ranking mechanism is an important service for e-commerce that facilitates consumers' decision-making process. Traditional services ranking methods ignore the fact that customers cannot rate services under the same criteria, which leads to the ratings are actually incomparable. In this paper, we propose to exploit the ordinal preferences rather than cardinal ratings to rank online services. Ordinal preferences are elicited from filled ratings so that the intensity of ratings is ignored. We construct a directed graph to depict the set of pairwise preferences between services. Then, the strongest paths of the directed graph are identified and the evaluation values of services are calculated based on the strongest paths. We prove our method satisfies some important conditions that a reasonable services ranking method should satisfy. Experiments using real data of movie ratings demonstrate that the proposed method is advantageous over previous methods, and so the proposed method can rank services effectively even the ratings are given by customers with inconsistent criteria. In addition, the experiments also verify that it is more difficult to manipulate the ranking result of our method than existing methods.

Keywords: Online services ranking · Ordinal preference · Inconsistent rating criteria · Manipulation

1 Introduction

The services in this paper refer to all kinds of online services, e.g., Web services, e-business services, mobile services and cloud services. Mobile service or electronic service using mobile devices and wireless telecommunications networks has become a hot topic in the information systems and marketing research community. And the great development of the Internet promotes the increase of services and competition dramatically. A consequence is that there are many services sharing the same or similar functions. Moreover, online service provision commonly takes place between parties who have never transacted with each other before, in an environment where the service consumer often has insufficient information about the service provider, and about the goods and services offered [1]. Then how to select

an optimal service becomes an important yet difficult problem to consumers. This problem can be mitigated through the use of service ranking. Therefore, reliable ranking measures of services are crucial for business applications.

Some people select services in accordance with the rank of reputation values. But, previous research on services ranking that based on reputation has included counting approach, probabilistic approach, fuzzy approach, flow approach [2, 3] etc. However, there is no consideration on users' preference or evaluation inconsistency in these methods. Some users prefer to give a higher rating to a certain service, while others prefer to give a lower rating because of the difference of consumers' psychology and background, which makes it impossible to compare one service's ratings from different users. For example, services with the same performance may get different ratings, while the previous researches make the services with the same performance get different evaluation results. Therefore, the ranking result of online services based on previous approach is actually incomparable because it lacks the objective representation of services quality. Only when the relationship of ratings assigned to different services by users is considered, will a comparable evaluation method be set up. In addition, the previous research needs only to give a high (or low) rating to one service repeatedly so that it can achieve the purpose of handling the service. Therefore, the ability of the previous research to prevent manipulation is small.

The contributions of the paper can be summarized as follows.

- (1) We explore the problem of ranking online services without considering the inconsistency of users' rating criteria and state the idea to address it by using Social Choice Theory. In this way, users' preference can be integrated with the way of aggregating ordinal preference without considering the problem that the ratings are given by users with inconsistent criteria.
- (2) We propose a Social Choice based services ranking algorithm, hereinafter to be referred to SCBSR algorithm. The proposed algorithm aggregates the ordinal preferences and returns the ranking results quickly to the user. We further prove that the result of proposed algorithm is hard to manipulate.
- (3) We prove some useful theorems so that the Social Choice Theory can be used to rank services with ordinal preferences. These theorems are closely related to users' consumption psychology, so that the efficiency of the algorithm can be improved.
- (4) We evaluate the rationality and validity of the proposed algorithms through a comprehensive experimental study and performance analysis.

The rest of paper is organized as follows. In Sect. 2 we review related work. In Sect. 3 we introduce some basic concepts and present a motivating example. In Sect. 4, we introduce the method in details and propose an algorithm to rank services. In Sect. 5, we prove some related theorems. In Sect. 6, we show a systematic empirical study. In Sect. 7, we conclude and discuss the future work.

2 Related Work

With the abundance and fast growth of online services available, how to rank services effectively has been a pressing problem which attracts lots of researchers doing valuable and interesting research [4, 5]. Related work in this area can be classified into two main streams [4]: ranking method based on attribute where the ranking is only related to the features of services, such as sales, price, reputation and ratings; and personalized ranking method.

- (1) Attribute-Based Ranking. Kai Hwang [6] combines the services attributes such as sale price, quantity ordered, delivery time, seller trust, and service quality to ranks sellers. S.N. Junaini [5] proposes a framework consisting of the usability factors such as simplicity, attractiveness, effectiveness, service image, site information, service details and so on to rank online services. Services are ranked based on each considered service feature, using text analysis techniques to extract condensed information from massive customer reviews in [7–9]. Some people also select services in accordance with the rank of reputation values [10]. Jiliang Tang obtains the user preference from users' reviews with changes over time, thereby compute the trust values of services and rank the services. *EBay*¹ computes the reputation of the service provide through collecting the feedback information from users after each transaction. Feedback information provided by users includes positive rating, neutral rating and negative rating. The reputation value is the result that the number of total positive ratings minus the number of total negative ratings. *Amazon*² also uses the feedback information to compute the reputation value. The only difference is the reputation value is the result of the average of all ratings. However, all of the researches mentioned above, whether based on the ranking of service feature or based on the ranking of reputation, involve the users' feedback information, but ignore the fact that the feedback information are given by customers actually incomparable. Moreover, some users maybe provide dishonest opinions. As a result, the result of ranking is subject to manipulation.
- (2) Personalized Ranking. In [11], services are ranked based on the users' own preferences and also on the information in the different search engines about the services. Ghose et al. [12] proposes a 'utility-preserving' ranking strategy from an economic perspective which takes multi-dimensional preference and customer heterogeneity into consideration. In [13], a new personalized service ranking method is proposed based on estimating consumer information search benefits and considering the uncertainty and confidence. All of these works ignore the relationship between different services, although some works take the users' preference into account. Different from these works, the approach proposed in our paper processes the ratings data firstly, rather than use it directly. Additionally, the approach takes the relationship among different services into account.

¹ <http://www.ebay.com/>.

² <http://www.amazon.cn/>.

3 Problem Description

In this section, we first describe the solution of the problem. Then we present a motivating example to highlight the focus of our study.

Definition 1: We let $U = \{u_1, u_2, \dots, u_m\}$ denote the set of users, $S = \{s_1, s_2, \dots, s_n\}$ denote the set of services; m is the number of users, n is the number of services.

Definition 2: $R = [r_{ik}]_{m \times n}$ denotes the ratings matrix of user-service, r_{ik} is the rating that user u_i rate the service s_k . When $r_{ik} = 0$, it indicates that user u_i has not yet rated the service s_k .

Definition 3: $O = \{o_k | k = 1, 2, \dots, n\}$ denotes the overall ranking of services. If $o_k > o_l$, it means the service s_k is better than s_l .

Clearly, an effective online services ranking method should satisfy the following criteria: (1) Condorcet: we define a Condorcet winner to be a service which beats every other service in pairwise matchups. (2) Monotonicity: increase one user's rating to a service shouldn't decrease their final ranking. (3) Non-Dictatorship: one user's preference shouldn't determine the outcome of the ranking. (4) Manipulation of Complexity: for any service s_l , the increase of users who only give the service s_l high rating and don't evaluate other services wouldn't change the result. (5) Majority Rule: the service s_k will be defined as the better one if the number of users who prefer service s_k to s_l are more than the number of users who prefer service s_l to s_k .

Example 1. As an example, we assume that there are 4 users (u_1, u_2, u_3, u_4) co-evaluating 3 services (s_1, s_2, s_3). The ratings matrix $R = [r_{ik}]_{4 \times 3}$ is showed in Table 1.

Table 1. Ratings matrix

r_{ik}	s_1	s_2	s_3
u_1	4	3	5
u_2	2	1	3
u_3	1	2	2
u_4	5	4	1

Using the summation method (referred to SUM) and the average method (referred to AVG) which are widely used in eBay, Amazon, Epinions, Taobao etc. well-known sites as comparison in the remainder of this paper. The results are shown in Table 2.

Table 2. The result of evaluation

	o_1	o_2	o_3	Ranking
Sum	0	-1	-1	$s_1 > s_2 \sim s_3$
Avg	3	2.5	2.75	$s_1 > s_3 > s_2$

With Table 1, we can know there are more than half of users preferring service s_3 to every other service, while only one user think service s_1 is better than service s_3 . According to the Condorcet, service s_3 is the best and should be ranked first. However, the results of SUM approach and AVG approach are different, believing s_1 is the first. Simultaneously, they violate the non-dictatorship. Moreover, if we add a new user who gives the service s_3 five points, then the service s_3 is ranked first. The non-manipulable is weak. Consequently, users cannot gain an accurate and stable ranking result. Thus, it is desired to develop a ranking approach that meets users preference and difficult to manipulate.

4 Ranking Online Services

Due to the inconsistent rating criteria and users' different subjective preferences, ratings given by different users are actually incomparable. And, users' rating for services is a personal utility. It cannot be measured or aggregated. So, the evaluation information that gathered by different user's rating cannot have cardinality. For all this, without considering the cardinal utility, we need to know the relationship of users' ordinal preference for services. Thus we should change the current social rating systems to enable each user to conduct a preference ranking of services based on evaluation instead of simply giving a rating after a transaction. But it will cost too much, and for users, require users to express the complete preference for all services will necessarily lead to problems of cost, cognitive, communication and privacy etc. Users cannot and will not provide the complete preference information.

Based on this, we firstly transfer the ratings into ordinal preference ranking for services through calculation, and then the number of users preference is obtained through aggregating the users preference. In this way, we avoid the problem that the ratings given by different users are actually incomparable. Lastly, we use the Schulze social choice function generates the online services ranking. Schulze social choice function is a voting algorithm proposed by Schulze Markus. The method can be used to generate a list of winners from users preference. In recent years, the Pirate Party of Sweden, the Debian project, the Wikimedia Foundation, the Gentoo project and other private organizations adopted the function for internal elections and referendum [14]. In this section, we firstly introduce the users preference obtaining. Then we describe our method in details and present the algorithm. Analysis and verification of the properties are provided in the next section.

4.1 Users Preference Obtaining

Since the services that users co-evaluated are few, the user-service ratings matrix is generally an incomplete set of entries. However, our method is based on the model of pair-wise comparisons, so it is necessary to fill the incomplete matrix. Considering the method of collaborative filtering is widely used, and different users have different preferences is an implicit assumption in the method [15], so we use the method to fill the incomplete matrix.

Based on the complete user-service ratings matrix, we calculate preference relations of each user for services, and establish preference matrix for each user. We express it as $LM_i[lm_{kl}]$, which is defined as:

$$lm_{kl} = \begin{cases} 1, & \text{if } r_{ik} > r_{il} \\ 0, & \text{if } r_{ik} = r_{il} \\ -1 & \text{if } r_{ik} < r_{il} \end{cases} \quad (1)$$

lm_{kl} denotes the users preference relationship between service s_k and service s_l . When $lm_{kl} = 1$, it means users prefer s_k to s_l . When $lm_{kl} = -1$, it means users prefer s_l to s_k . When $lm_{kl} = 0$, it means users think s_k and s_l have no difference.

According to the preference matrix of each user, we count the number of $lm_{kl} = 1$ in m users so that we can get the ordinal preferences. And we express it as comparative matrix of service-service $CM[cm_{kl}]_{n \times n}$ ($k, l = 1, 2, \dots, n; k \neq l$), which is defined as:

$$cm_{kl} = \sum_{i=1}^m lm_{kl}. \quad (2)$$

cm_{kl} denotes the amount of users who prefers s_k to s_l .

4.2 Social Choice Based Services Ranking Algorithm

For making the algorithm clear and understandable, we introduce some more definitions as follows:

Definition 4: We define a directed graph $G = (V, E)$ such that $V = S$ is the set of vertices, and E is the set of edges, which is defined as the set $\{(s_k, s_l) \in V \times V\}$. The weight of edge is the value of cm_{kl} and $cm_{kl} \geq cm_{lk}$.

Definition 5: We use a sequence of services set $\{s(1), s(2), \dots, s(t)\} \subseteq S$ denotes a path from service s_k to service s_l and it must satisfy the following characteristics:

- ① $s(1) = s_k, s(t) = s_l$
- ② $0 \leq t \leq n$
- ③ $\forall t = 1, \dots, n-1: cm_{s(t), s(t+1)} > cm_{s(t+1), s(t)}$ and $s(t) \neq s(t+1)$

The algorithm starts with the comparative matrix of service-service CM we calculated above. Then, based on the Definitions 4 and 5 we look for the strongest path from service s_k to s_l and express it as the strongest path length matrix $PM[p_{m_{kl}}]$. The values of the strongest path $p_{m_{kl}}$ have three cases, as follows:

- ① If there is no path from vertex s_k to vertex s_l , then there is also no strongest path from service s_k to service s_l and $p_{m_{kl}} = 0$;
- ② If there is only one path can be reached from vertex s_k to s_l , then this path is the strongest path from the service s_k to service s_l and the minimum weight in this path is the value of the strongest path, that is $p_{m_{kl}} = \min(cm_{s(i), s(i+1)}), i = 1, \dots, t-1$;

- ③ If there are multiple paths to reach from vertex s_k to vertex s_l , then compared the minimum weight of each path, the maximum value of that path is the strongest path from service s_k to service s_l . So $pm_{kl} = \max\{\min(cm_{s(i),s(i+1)})\}$, $i = 1, \dots, t-1$.

Then we calculate the evaluation values of services based on the strongest path length matrix, that is $o_k = \sum_{l=1}^n (I(pm_{kl} > pm_{lk}))$, $l = 1, 2, \dots, n$, and $I(*)$ is a indicate function.

$$I(pm_{kl} > pm_{lk}) = \begin{cases} 1, & \text{if } pm_{kl} > pm_{lk} \\ 0, & \text{others} \end{cases} \quad (3)$$

As can be seen from above, the evaluation results of the services depend on the quantity of this service's strongest path value more than others. Finally, we can get the whole ranking of services by sorting the evaluation values of each service. Algorithm 1 is our SCBSR algorithm.

Algorithm 1: SCBSR algorithm

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 $cm_{kl}$ , the value of comparison of two services from item
 $k$  to item  $l$  (Input)
 $O$ , the overall ranking of services (Output)
begin
  for  $k$  from 1 to  $n$ 
    for  $l$  from 1 to  $n$ 
      if ( $k \neq l$ ) then
        if ( $cm_{kl} \geq cm_{lk}$ ) then
           $pm_{kl} := cm_{kl}$ ;
        else  $pm_{kl} := 0$ ;
  for  $t$  from 1 to  $n$ 
    for  $k$  from 1 to  $n$ 
      if ( $t \neq k$ ) then
        for  $l$  from 1 to  $n$ 
          if ( $t \neq l$  and  $k \neq l$ ) then
             $pm_{kl} := \max(pm_{kl}, \min(pm_{kt}, pm_{tl}))$ ;
  for  $k$  from 1 to  $n$ 
    count:=0;
    for  $l$  from 1 to  $n$ 
      if ( $pm_{kl} \neq 0$  or  $pm_{lk} \neq 0$ ) then
        if ( $pm_{kl} > pm_{lk}$ ) then
          count:=count+1;
     $o_i := \text{count}$ ;
  sort( $o_i$ );
end.

```

Applying the above algorithm to Example 1 in Sect. 3, the ranking result is $s_3 > s_1 > s_2$. Table 1 shows that more than half of users think that service s_3 is better than the other services, while only one user think service s_1 is better than service s_3 . According to the Condorcet and Non-dictatorship, service s_3 is the best and should be ranked first, consistent with the results. So, Example 1 satisfies Condorcet and Non-dictatorship.

5 Theoretical Analysis of Ranking Model

In this section we prove our method satisfies Condorcet, monotonicity, and non-dictatorship condition. The complexity of manipulation of the rank results also be analyzed.

Theorem 1 (Condorcet). For any service s_k , when more than half of users think that service s_k is better than every other service in pairwise matchups, then s_k is Condorcet candidate.

Proof: When more than half of users think that service s_k is better than other services, it is obvious that $cm_{kl} > cm_{lk}$. So there is no path that treats other services as vertex point to service s_k . So $pm_{kl} > pm_{lk}$ for any $l = 1, 2, \dots, n$, namely, service s_k is the best, featuring Condorcet. Condorcet meets most people's preference, embodying the will of the majority of people. So we can also treat the Condorcet candidate as evaluation result to recommend.

Theorem 2 (Monotonicity). When users' preference are invariable and their ranking for any service s_k and s_l is as $s_k > s_l$ (denotes service s_k is better than s_l). If a certain user upgrades his/her rating for service s_k , then the ranking of service s_k will be unchanged or move ahead compared to s_l , featuring monotonicity.

Proof: If a certain user upgrades his/her rating for service s_k , then the number of users who think the service s_k is better than s_l increases. So the value of cm_{kl} increases. Then the minimum strength of the path that starts with the service s_k point to service s_l is impossible to reduce. Thus the value of pm_{kl} is impossible to reduce. So $pm_{kl} > pm_{lk}$ is unchanged, namely, the entire ranking is maintaining the ordering as $s_k > s_l$. Thus this method satisfies monotonicity. Monotonicity highlights the stability of ranking, and it wouldn't decrease the rankings of service by increasing the number of users who think a service is better than other services.

Theorem 3 (Non-dictatorship). If and only if there is one people believes s_k is better than s_l , while others believe that s_l is better than s_k . When the result is the ranking of s_l no worse than s_k , the non-dictatorship can be satisfied.

Proof: When there is only one people thinking s_k is better than s_l , according to Formulas (1) and (2), $cm_{kl} = 1, cm_{lk} > 1$. So the strength of the path that begin with the service s_l point to service s_k is greater than 1. Thus $pm_{lk} > 1, pm_{lk} \geq pm_{kl}$, so service s_l will not inferior to s_k . Thus this method satisfies non-dictatorship. Non-dictatorship guarantees that the users' specific preferences don't affect overall evaluation results.

Theorem 4 (Manipulation of Complexity). For any service s_l , the increase of users who only give the service s_l high rating and don't evaluate other services wouldn't change the result.

Proof: According to the ranking method of this paper, we need to fill the user-service ratings matrix of incomplete. However, according to the method of collaborative

filtering, the filling data by calculated is equal to the rating that new users have given to service s_l , so the value of cm_{kl} is unchanged; the value of pm_{kl} is also unchanged. Thus the ranking result maintains unchanged. Therefore, when you tend to manipulate one service, the method of service evaluation in this paper is more complex than the existing methods.

6 Experiment and Analysis

In this section, we through verifying the Condorcet, monotonicity, majority rule, and complex of manipulation of the ranking results to test the effectiveness and rationality of online services rank method. All experiments were conducted on a PC with Intel Core i3 3.50 GHz CPU and 8 GB of RAM. The algorithms are implemented in MyEclipse 2015.

To verify the validity of method, we have used a movie data set with the real ratings: MovieLens³ which has 1682 movies, 943 users and 100 thousand ratings. In the experiment, to ensure the movie that users have common rated have a certain number, and in order to compare the advantages and disadvantages with other methods on different sparsties, it is necessary to filter on datasets. Five groups of different datasets were obtained after processing the initial data.

6.1 Condorcet

If the first service ranked by this method is equal to the Condorcet candidate, then this method satisfies Condorcet property. Aggregating all users' preferences, we can know that more than half of users think the service 47# is better than any other services, so the service 47# is Condorcet candidate. The result has been shown in Fig. 1, the evaluation value of service 47# is the biggest, ranking first. Consistent with theoretical analysis result, so this method satisfies the Condorcet property.

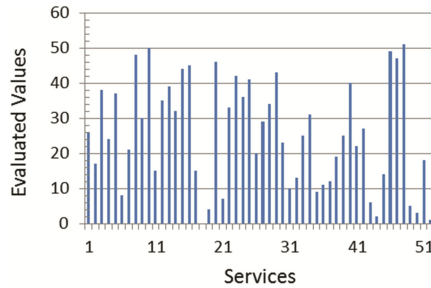


Fig. 1. Condorcet verification

³ <http://www.grouplens.org/node/73>.

6.2 Monotonicity

In order to verify the monotonicity of our method, the paper selects a service randomly and increases its rating, to judge whether the ranking of the service is changed. If the place of this service is ahead or unchanged, then the monotonicity of this method is verified. In the experiment, taking service 1# and service 2# as examples, service 1# is better than service 2#. After we increase the rating rated by users to service 1#, evaluation value of service 1# is increases, while the evaluation value of service 2# and other services remains unchanged. The result has been shown in Fig. 2. So the final ordering of service 1# is still ahead of service 2#, and compared to the rankings of other services, the ranking of service 1# can only be ahead or unchanged but not lower, verifying the monotonicity of this method.

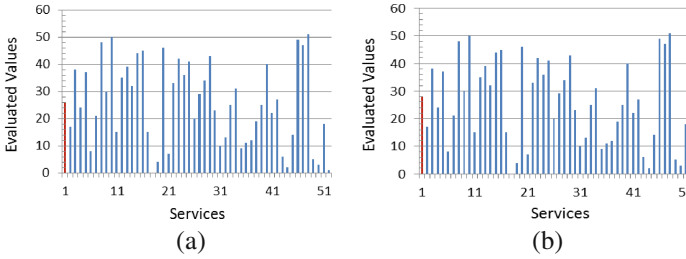


Fig. 2. Monotonicity verification. (a)Before change (b) After change

6.3 The Complexity of Manipulation

In order to verify the complexity of manipulation of the method, the paper chooses a service randomly and increases several users' rating for the service. Compared with other methods, if our method has the same results and the other methods make the ranking values of this service move ahead, then our method satisfies the complexity of manipulation. In this section, we conduct two sets of experiments. A set of experiments assumes that the number of users is constant, increasing the rating. So we assume that 10 users give the service 7# 5 points, 4 points, 3 points, 2 points, 1 point in turn to observe the rankings of the service, as shown in Fig. 3(a). Another set of experiments assumes that the rating is constant, increasing the number of dishonest users. So we assume these users give the service 7# 5 points, then increasing the number of dishonest users. The result of the rankings of the service has shown in Fig. 3(b). According to Fig. 3, we know no matter how we try to change, the ranking of service 7# remains unchanged, while the rankings in other two methods is increase or decrease, achieving the purpose of manipulation. So our method is more difficult to manipulate than the others.

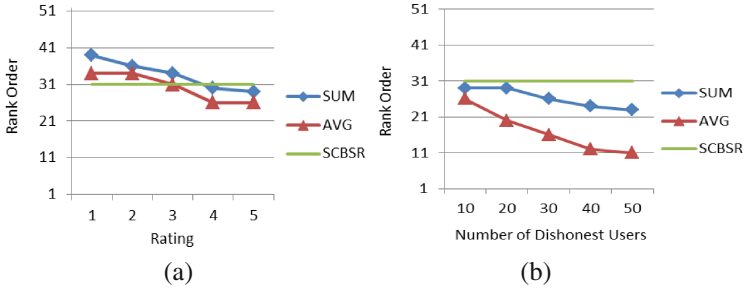


Fig. 3. The complexity of manipulation verification. (a) Increase ratings (b) Increase the number of dishonest users

6.4 Majority Rule

According to the herd mentality of the consumer, we verify the majority rule of economics theory. That is to say, when all of services are for pairwise comparison, the result of ranking is s_l superior to s_k if the number of users who prefer service s_k to service s_l are more than the number of users who prefer service s_l to service s_k . But because of Condorcet's Paradox, the results cannot be reached 100 %. In this section, we count Majority Rule ratio of three methods by testing five groups of different datasets. As shown in Fig. 4, our method achieving on 99 % accuracy, higher than the other two methods.

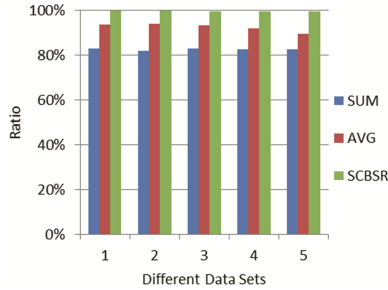


Fig. 4. Majority rule verification

6.5 Response Time

When the number of services is fixed, we increase the number of users in turn, and record the response time of the system for ranking all of services. As shown in Fig. 5, with the increase of the number of users, the response time of the system is approximately in a linear speed increase. As the number of users increases, the amount of calculation for the overall ranking will increase, but our ranking method did not lead to the response time increasing in exponentially, so our method is more efficient. And the Fig. 5 shows that our method has a long system response time compared with the other two methods.

On the other hand, manipulating the ranking results of our method takes longer than the other two methods, so our method is more difficult to manipulate than the others.

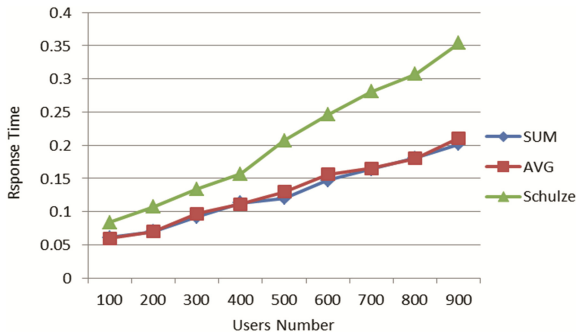


Fig. 5. The response time of system

7 Conclusion

In this paper, we address the problem of users rating criteria inconsistent-based services ranking. We firstly transfer the ratings in current social rating systems into users' preference ranking for services through calculation. Then we propose an algorithm based on social choice theory to get the services ranking. By this way, we get the ordinal preferences without changing the current ratings system. Additionally, the approaches take the relationship between different services into account, rather than some separate services as the evaluation objects. Lastly, we apply theoretical analysis and experiment to verify the Condorcet, monotonicity, un-dictatorship and complex of manipulation of our approach. In the future work, we will further study the ranking services method under the condition of not filling the matrix.

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